EXPERIMENTAL CHARACTERIZATION OF ULTRASONIC PHENOMENA BY A NEURAL-LIKE LEARNING SYSTEM

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ABSTRACT

This paper describes a novel approach for analyzing ultrasonic signals to permit an experimental determination of the relations between elastic wave phenomena and the properties of a source of sound in a material. It is demonstrated that an adaptive learning system comprising an associative memory can be used to map source and waveform data and vice versa with the auto- and cross-correlation portions of the associative memory. Experiments are described which utilize such an adaptive system, running on a laboratory minicomputer, to process the data from a transient ultrasonic pulse in a plate specimen. In the *learning* procedure, the system learns from experimental pattern vectors, which are formed from the ultrasonic waveforms and, in this paper, encoded information about the source. The source characteristics are recovered by the *recall* procedure from detected ultrasonic signals and vice versa. Furthermore, from the *discrepancy* between the presented and the learned signals, the changes in the wave phenomenon, corresponding, for example, to changes in the boundary conditions of a specimen, can be determined.

INTRODUCTION

The past decade has seen the development of truly *quantitative* active (UT) as well as passive (AE) ultrasonic techniques whose application is to a number of non-destructive test methods (c.f. [1,2]). The experimental research has been supported by the development and application of various electronic devices, such as broadband transducers, waveform digitizers and laboratory computers, which facilitate the transition from empirical to quantitative physical characterization of a broad range of materials and deformation properties. At the same time, a theoretical description of the corresponding wave phenomenon has been developed on the basis of elastodynamic theory, which has enabled a physical modelling of acoustic events, a comparison between theoretical and experimental results and has permitted finding in several cases, a solution to an inverse problem. Unfortunately, the existing solutions of the inverse problem are so complicated that, in spite of their apparent correctness, they appear to be only practical for laboratory measurements [3]. It is for this reason that in current NDT practice, the phenomenological relations between ultrasonic signal parameters and characteristic state variables continue to be used instead. Unfortunately, this makes it impossible to describe and to model the physical mechanisms taking place at a source of ultrasound in a material. The aim of this paper is to represent a novel method for characterizing ultrasonic wave phenomenon, which bridges the gap between a phenomenological and a physical description. For this purpose, an intelligent system is utilized, resembling the structure of a neural network. The system operates similarly to a primitive intelligent being: in a *learning mode* of operation, it receives the information about various possible ultrasonic signals and utilizes this information later during the *analysis mode* of operation to extract physical properties either of the source or of the wavefield. Alternatively, it can be used to give an exact physical description based on elastodynamical theory.

QUANTITATIVE ULTRASONIC MEASUREMENTS

The goal of quantitative ultrasonic measurements may be the characterization of the source (AE), the characterization of the medium (UT) or the characterization of the receiver (sensor calibration) from the signals detected on the surface of a specimen [2]. If the elastic waves emanating from a given source can be described by the displacement field vector, $\mathbf{u}(\mathbf{r},t)$, then from elastodynamic theory it follows that the displacement field components u_i detected at a receiver location, $\mathbf{r}$, in a structure from an arbitrary point source of density $\mathbf{f}(\mathbf{r}', t)$ located at $\mathbf{r}'$ having source volume V_0 can be written as [4]

$$u_i(\mathbf{r},\ t) \ = \ \int_{V_0} \int_0^t f_j(\mathbf{r}',\ \tau) G_{ij}\ (\mathbf{r}|\mathbf{r}';\ t-\tau)\ d\tau\ dV'$$

which can be expressed in abbreviated form as,

$$\mathbf{u} \ = \ \mathbf{f} \ * \ \mathbf{G} \tag{1}$$

where $*$ indicates a convolution operation. The integral appearing in the above equation extends over space and time with the term G_{ij} representing the dynamic Green's function of the structure. In the equations, the source of ultrasound is completely described by the force density, $\mathbf{f}(\mathbf{r},t)$. The emanating ultrasonic wavefield can be determined from it by a generalized convolution expressed by Eqs. (1) provided that the Green's tensor $G_{ij}(\mathbf{r}|\mathbf{r}';t)$ is known. In the inverse source problem, the force density, $\mathbf{f}$, is recovered from the measured displacement field, $\mathbf{u}$, and the Green's tensor. In this case, the integral equation given by Eq. (1), must be solved, often with noise-corrupted data from a finite number of sensors. This represents an ill-posed inverse problem for which approximate methods of solution have been developed by making use of various regularization principles (c.f. [5]). That is, in order to recover the force density, one must deconvolve the ultrasonic displacement data with the inverse Green's function according to

$$\mathbf{f} \ = \ \mathbf{u} \ * \ \mathbf{G}^{-1} \tag{2}$$

where $\mathbf{G}^{-1}$ denotes the inverse Green's function. While this procedure has been demonstrated for various simulated and real AE sources, it is experimentally and computationally a prohibitive task for most practical applications. It is for this reason that we explore the use of a neural-like processing scheme as an alternative. We briefly describe here the basis of the processing scheme whose application can be to obtain a solution to inverse source and possibly inverse medium problems. It has been shown that such processing yields an optimal solution to an inverse problem from the given data [6]. Analogous to the sensor-neural systems possessed by living beings in which past sensed signals (visual or aural) are stored in the brain, we demonstrate here the use of the associative properties of neural networks to process ultrasonic signals.

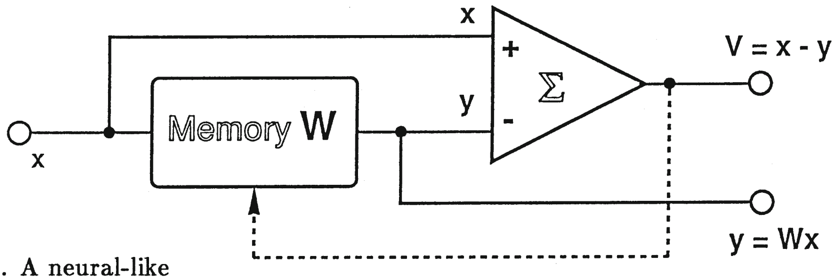

Figure 1. A neural-like processing system.

NEURAL-LIKE ULTRASONIC SIGNAL PROCESSOR

Our application of this approach is shown schematically in Fig. 1. Its features, which have been described in several publications [6,7,8], use some of the fundamental principles of neural networks [9]. Briefly, we assume that an ultrasonic wavefield can be characterized by a finite set of data supplied from an array of sensors together with selected features of the source, structure or sensor. For one experiment in which data is collected with Q sensors, the *pattern* vector is given by

$$X = \{v^{(1)}(t),\ v^{(2)}(t), \ldots, v^{(Q)}(t);\ g\} \tag{3}$$

which is applied as input to the processor shown in Fig. 1 where the $v^{(q)}$ represents the discretized signal detected by the q-th sensor and g are elements in which is encoded specific information about one or more of the components comprising the ultrasonic system. In this paper, we are restricting this to the source of ultrasound. In a series of experiments, one obtains the ensemble of pattern vectors $\{X_n\}$.

For each fixed input vector from this ensemble, the system responds with an output vector Y which is of the same dimension as X and which can be determined from the linear matrix equation

$$Y = \mathbf{W} \cdot X \tag{4}$$

where the matrix $\mathbf{W}$ represents the response function or *memory* of the system. In order to obtain an *associative* operation of the processing system, we assume that the system adapts to the input vectors such that the *discrepancy* or *novelty* between the input and output vectors, given by

$$V = X - Y = X - \mathbf{W} \cdot X \tag{5}$$

is reduced with a repetition of the inputs. This is possible with the feedback loop shown in Fig. 1. The adaptive law of the system which governs how the memory develops is similar to that used in other applications and is expressed by [10]

$$\Delta \mathbf{W} = CV \otimes X^T \tag{6}$$

Here C is an *adaptation* constant and X^T denotes the transposed pattern vector. The convergence and rate of the iteration procedure is controlled by the constant C which must be selected in the interval:

$$0 < C < 2/\mid X \mid^2 \tag{7}$$

If the pattern vectors are normalized to 1.0 then the fastest learning is obtained with constant $C = 1$. At the beginning of the adaptation each presented pattern is essentially learned in its first presentation to the system.

It is seen that as input vectors are presented to the system, the result is the formation of the memory matrix $\mathbf{W}$ from an initially empty state, i. e. $\mathbf{W_0} = 0$. This resembles a *learning* process during which the system adapts to the input so that the output vectors resemble the input vectors. If a new input vector is presented to the system, the generated output vector is a linear mixture of all the previously presented pattern vectors which most closely correlate to the new one.

On the other hand, if the processing system is presented a new pattern vector which is similar to a previously presented one but with some of the components missing, then the output vector will contain those components from that previously presented pattern vector which most closely resembles the unknown. As such, one can use this processing procedure to obtain a solution to the forward elastodynamic problem from input of the source characteristics, or one can use it to obtain a solution to the inverse source problem from the ultrasonic signals presented to it. Such a recall is characteristic of an *associative* operation of intelligent systems [11]. In a biological neural system the synapses between neurons are adaptively changed during learning [9,10]. Hence, the processing system described here resembles a neural network with the matrix $\mathbf{W}$ representing synaptic weights [10,12].

EXPERIMENTS

The proposed neural-like ultrasonic signal processing system was simulated on a laboratory computer. The pattern vectors were generated from 150 components of which 128 were selected to represent the detected ultrasonic signals while the remaining 22 components were used to encode information about the source.

The operation of the processing system has been demonstrated with ultrasonic waveforms obtained in several simple source location and source characterization problems as well as an ultrasonic wavefield measurement situation [6,7]. More specifically, they have included: Linear and two-dimensional source location problems, combined one-dimensional source location and scalar source characterization problems, the characterization of simple vector sources and the detection of changes in the boundary of a specimen. Some of the measurements were made using a thick, anisotropic graphite-epoxy composite for which no Green's function is yet available [13]. For most of the results presented here, the experimental setup consisted of a 1-inch thick, flat aluminum plate, 30 inches on edge with an array of miniature, broadband piezoelectric sensors mounted on its surface. The source of the ultrasonic signals was obtained from the impact of a steel ball on the surface. The signals from the sensors were amplified by 40 db and recorded by a multi-channel waveform recording system, which was triggered by a signal from a separate digitizer. The sampling rate was 2 MHz. The data record length of 1024 points from each sensor was reduced to 64 so that the data from both sensors could be concatenated to form the 128-point waveform component of the pattern vector.

The first experiment to be described is a linear AE source location problem. Here the two sensors were spaced 20 inches apart. The AE signals were simulated by dropping a steel ball of 8 mm diameter from a height of 5 mm. Learning was performed with 19 signals excited on the line between both sensors at positions spaced 1 inch apart. The detected signals are shown in Fig. 2(a). The corresponding encoded source positions are shown in Fig. 2(b) and the completed input pattern vectors are shown by solid lines in Fig. 2(c). During the iterative learning procedure, the output vectors denoted by the dotted lines in Fig. 2(c) were learned. Good agreement between input and output vectors indicates correct adaptation of the system. The memorized response matrix $\mathbf{W}$ is shown in Fig. 2(d). There are nine characteristic regions in the matrix, corresponding to auto- and cross-correlations between the parts constituting the pattern vectors comprised of the data from the two sensors and the encoded source information. Each portion of the memory is of importance for the associative operation of the system during an analysis of new patterns presented to the system.

When the signals are analyzed by the adapted system it is convenient to fix the response matrix $\mathbf{W}$ by turning off the feedback to the memory. In order to demonstrate the associative operation of the system, we have presented to it the pattern vectors comprising only the AE waveforms which were shown in Fig. 2(a). The corresponding response vectors are shown in Fig. 3. It is evident that the peaks characterizing the missing source information are properly recovered by the associative recall. It is noted however, that the recalled signals are not exact copies of the corresponding complete vectors but appear to be slightly noisy. This effect is a consequence of the similarity between various input vectors. In spite of this, the correct source position is determined from the recalled vectors. This is also the case if input signals, obtained in a new set of experiments, even with added noise, is presented to the processor.

The same system is also applicable for the associative recall of waveforms, that is, for obtaining a solution to the forward elastodynamic problem. For this, the input vectors contain only the encoded source characterization, as shown in Fig. 2(b). After processing, the output vectors, shown in Fig. 4, also contain those portions corresponding to the AE signals which have been associatively recalled from memory.

The system has also been trained with two source parameters - source location and impacting ball size. In these experiments, two balls, 4 and 6 mm in diameter, were used as the excitation at points along the line connecting the two sensors. The source position and ball radius were encoded into the pattern vector. After completing the learning procedure, the system was presented input vectors which were comprised of only the AE signal portions. The peaks representing the encoded source properties were again correctly recalled. A similar experiment has been carried out with impacts on a thick, slightly curved, anisotropic composite plate [13]. In these experiments, the system was also presented signals corresponding to impacts at positions which

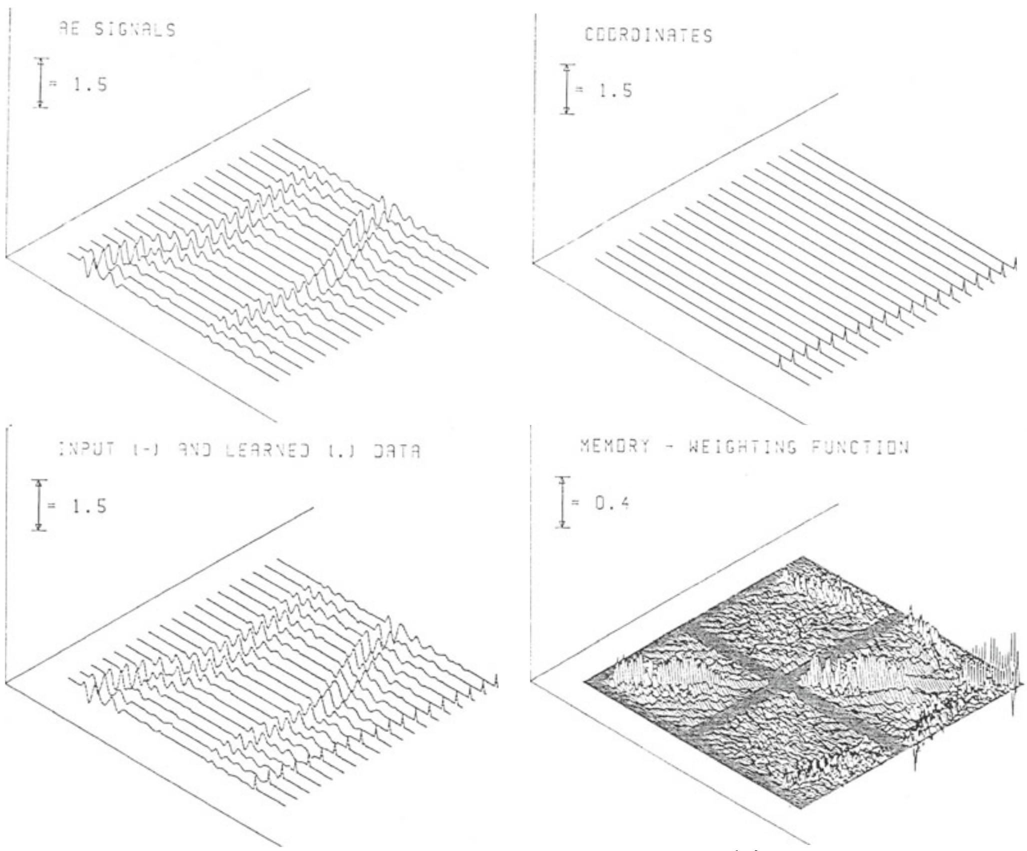

Figure 2. Linear source location; (a) Detected AE waveforms; (b) Encoded source location data; (c) Input, recovered pattern vectors; (d) Memory matrix **W**.

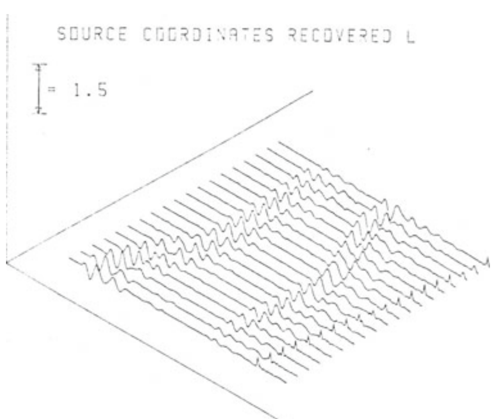

Figure 3. Recovered source parameters.

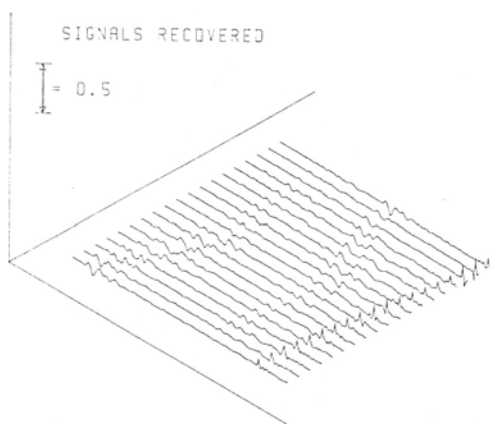

Figure 4. Recovered waveforms from source data.

were not previously learned by the system. Even for these, the system was able to recover an approximate value of the source location and ball size.

In addition to the results presented here, experiments were also completed with four transducers in a square array used to locate in 2-dimensions sources of emission in its interior [7]. Another application of the processing scheme has been to characterize the components of a vector source. For this, the fracture of pencil leads activated in various directions along one edge of a 3-inch thick aluminum block was used [6]. An array of four sensors on the top surface of the block detected the simulated AE. After learning, the system correctly processed the waveforms to recover the different source orientations and positions along the edge.

Preliminary experiments were carried out with the neural-like processing approach to detect changes in the wave propagation in a specimen. For studying this, two transducers were mounted 50 mm apart on the plate. The impact of a steel ball, 1.6 mm in diameter, dropped from a height of 30 mm was used as a source on the line joining both sensors. In the analysis mode, a brass disc, 22 mm in diameter and 12 mm thick was coupled by means of silicone oil at different positions onto the bottom side of the plate at points between the source and the receivers. The source was activated at the previous source points. The effect of the attached disk on the surface is to very slightly alter the boundary condition which appears as a slight variation in the measured ultrasonic wavefield relative to the original measurements. To detect the changes in the signals, the discrepancy vector, V, was used. As expected, the discrepancy between the learned and new patterns is highest when the disk is attached approximately in the middle of the interval between the source and receiving transducers. This demonstrates that an adaptive system can be used in non-destructive testing applications in which changes caused by variable wave impedances, such as the development and growth of defects in a structure are to be detected.

CONCLUSIONS

We have shown in this paper that an adaptive learning system comprised of an associative memory can be used to map ultrasonic source and waveform data and vice versa with the auto- and cross-correlation portions of the memory. Experiments were described utilizing such an adaptive system, to process the data of ultrasonic pulses in a plate specimen. In the *learning* procedure, the system developed the memory from experimental pattern vectors, comprised of waveform and source data. The source characteristics were recovered by the *recall* procedure from detected ultrasonic signals and vice versa. From the *discrepancy* between the presented and the learned signals, the changes in the wave propagation could be characterized.

The application of neural-like processing of waveforms appears to be a promising means for the processing ultrasonic signals. But it need not be restricted to such waveforms for it can also be applied to process the signals detected with other NDT techniques in which multi-component signals need to be processed. Because of our limited resources, the system we have described has been simulated on a laboratory minicomputer, but its structure makes it ideal for a fully parallel processing operation as in a neural network. This is of advantage when the speed of operation or the number of components to be recovered is appreciably large. We believe that the encouraging results we have obtained with our measurement system represents the foundation for the development of a completely new generation of intelligent NDT/NDE signal analyzers resembling neural networks.

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